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Conference Abstract

The PEcAn+SIPNET Terrestrial Carbon Cycle Reanalysis: Development and Validation

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Abstract

Improving our ability to understand and predict the dynamics of the terrestrial carbon cycle remains a pressing challenge despite a rapidly growing volume and diversity of Earth Observation data. State data assimilation represents a path forward via an iterative cycle of making process-based forecasts and then statistically reconciling these forecasts against numerous ground-based and remotely-sensed data constraints into a “reanalysis” data product that provides full spatiotemporal carbon budgets with robust uncertainty accounting. Here we report on an >100x expansion of the PEcAn+SIPNET reanalysis from 500 sites CONUS, 25 ensemble members, and 2 data constraints to 6400 sites across North America, 100 ensemble members, and 5 data constraints: GEDI and Landtrendr AGB, MODIS LAI, SoilGrids Soil C, and SMAP soil moisture. We also report on an ensemble-based machine learning (ML) downscaling to a 1km product that preserves spatial, temporal, and across-variable covariances and demonstrate the impacts of these covariances on uncertainty accounting (Fig. 1). Synergistically, we use the same ML models to assess what climate, vegetation, and soil variables explain the spatiotemporal variability in different C pools and fluxes. In addition, we review a wide range of ongoing validation activities, comparing the outputs of the reanalysis against withheld data from: Ameriflux and NEON NEE and LE; USFS Forest Inventory biomass,

biomass increment, tree rings, soil C, and litter; and NEON soil C and soil respiration. Finally, we touch on ML analyses to diagnose and correct systematic biases and emulator-based recalibration efforts.

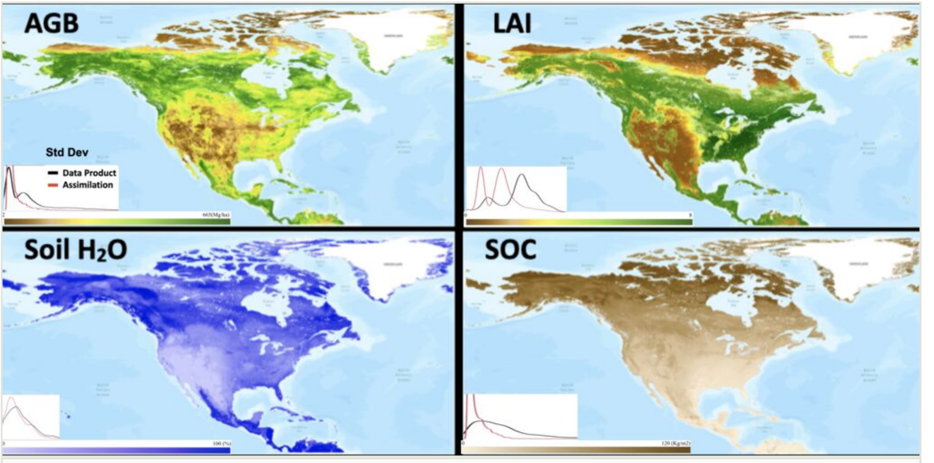

Figure 1. doi

Example downscaled reanalysis maps for June 2021 and associated uncertainty reductions compared to individual data products.

Keywords

Ecological forecasting, data assimilation, model-data fusion

Presenting author

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Presented at

KEYNOTE

Conflicts of interest

The authors have declared that no competing interests exist.